

wCorr Proofs

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2016-11-21

Proof of consistency of Horvitz-Thompson estimator of a mean.

An Horvitz-Thompson (HT) estimator of a sum takes the form

$$\hat{Y} = \sum_{i=1}^n \frac{1}{\pi_i} y_i , \quad (1)$$

where there are n sampled units from a population of N units, each unit has a value $y \in \mathfrak{R}$, each unit is sampled with probability π_i , and \hat{Y} is the estimated of Y in a population. Probabilistically, the formula is

$$\hat{Y} = \sum_{i=1}^N I_i \frac{1}{\pi_i} y_i , \quad (2)$$

where I_i is one when a unit sampled and zero otherwise. Notice that

$$E(I_i) = \pi_i , \quad (3)$$

and that the covariance of two units ($\text{Cov}(I_i, I_j)$ for $i \neq j$) is not assumed to have any particular structure.

Unbiasedness of Horvitz-Thompson estimator

Given:

1. $\frac{n}{N} = v$, for some $v \in \mathfrak{R}$,
2. $\frac{1}{\pi_i} > 0 \forall i \in \{1, \dots, N\}$

It is simple to see that

$$E(\hat{Y}) = \sum_{i=1}^N \frac{E(I_i)}{\pi_i} y_i \quad (4)$$

$$= \sum_{i=1}^N y_i \quad (5)$$

$$= Y \quad (6)$$

Decreasing variance of the Horvitz-Thompson estimator

The the variance of the HT estimator is, switching to the now more convenient notation where $w_i = \frac{1}{\pi_i}$

$$\text{Var}(\hat{Y}) = \text{Var}\left(\sum_{i=1}^N I_i w_i y_i\right) \quad (7)$$

$$= \sum_{i=1}^N \text{Var}(I_i) w_i^2 y_i^2 + \sum_{i=1}^{N-1} \sum_{j=i+1}^N w_i y_i w_j y_j \text{Cov}(I_i, I_j) . \quad (8)$$

Because the I_i has a Bernouli distribution, $\text{Var}(I_i) \leq 1/4$. To bound the covariance terms, consider building the variance of the sum elementwise. First, define

$$A = \sum_{i=1}^{m-1} y_i \quad (9)$$

$$B = y_m \quad (10)$$

then

$$\text{Var}\left[\left(\sum_{i=1}^{m-1} y_i\right) + y_m\right] = \text{Var}(A + B) \quad (11)$$

$$= \sigma_A^2 + \sigma_B^2 + 2\sigma_{AB} , \quad (12)$$

where σ_A^2 is the variance of A , σ_B^2 is the variance of B , and σ_{AB} is the covariance of A and B . The formula that relates the correlation coefficient ρ to the standard deviations and covaraince is

$$\rho = \frac{\sigma_{AB}}{\sigma_A \sigma_B} \quad (13)$$

$$\sigma_A \sigma_B = \frac{\sigma_{AB}}{\rho} \quad (14)$$

this is clearly maximized when ρ is one in magnitude and has the same sign as σ_{AB} so that

$$\sigma_A \sigma_B \leq |\sigma_{AB}| \quad (15)$$

plugging that into (12) results in

$$\text{Var}(A + B) \leq \sigma_A^2 + \sigma_B^2 + 2\sigma_A \sigma_B , \quad (16)$$

define $k \in \Re$ such that

$$\sigma_B = k\sigma_A \quad (17)$$

then (??) becomes

$$\mathrm{Var}(A+B) \leq \sigma_A^2 + k^2 \sigma_A^2 + 2k \sigma_A^2 , \tag{18}$$

$$= \sigma_A^2 (1 + 2k + k^2) . \tag{19}$$